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Triona S. Matheson

University of Portland, matheson18@up.edu

Brian Satterthwaite

University of Portland, satterth17@up.edu

Hannah Callender Highlander

University of Portland, highland@up.edu

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Cover Page Footnote

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Modeling the Spread of the Zika Virus at the 2016 Olympics

Triona Matheson¹, Brian Satterthwaite², Hannah Callender Highlander^{2,*}

*Correspondence:
Prof. Hannah Callender
Highlander,
Dept. of Mathematics,
University of Portland,
5000 N Willamette Blvd.,
Portland, OR 97203, USA
highland@up.edu

Abstract

The Zika Virus is an arbovirus that is spread by mosquitoes of the *Aedes* genus and causes mild fever-like symptoms. It is strongly associated with microcephaly, a condition that affects development of fetal brains. With the recent emergence of Zika in Brazil, we develop an agent-based model to track mosquitoes and humans throughout the 2016 Olympics in Rio de Janeiro to investigate how the Olympics might affect the spread of the virus. There are many unknowns regarding the spread and prevalence of Zika, with approximately 80% of infected individuals unaware of their infectious status. We therefore discuss results of experiments where several unknown parameters were varied, including the rate at which mosquitoes successfully bite humans, the percentage of initially infected mosquitoes, and the sizes of the human and mosquito populations. From these experiments, we make initial predictions regarding effective control measures for the spread of Zika.

Keywords: agent-based modeling, Zika virus, 2016 Olympics, SEIR model, sensitivity testing

1 Introduction

The Zika Virus

The Zika Virus is an arbovirus (arthropod borne virus) that was first isolated from a monkey in the Zika forest of Uganda in 1947 [19]. Zika is of the *Flaviviridae* family that includes other arboviruses such as Dengue, Yellow fever, and West Nile [11], each of which are also spread by the same arthropod vector: the *Aedes aegypti* mosquito and other mosquitoes of the *Aedes* genus. These mosquitoes live primarily in tropical regions. The primary route of infection of Zika is through skin cells, which are permissive to infection by Zika when a human is bitten by an infectious mosquito [11]. Symptoms of Zika include fever, rash, joint pain, and conjunctivitis, but symptoms are often very mild and last a few days to a week [25].

The first major outbreak of Zika occurred in 2007 on Yap Island in a territory of the Federated States of Micronesia [11]. The outbreak lasted a few months, and by the end of it, up to 75 percent of the population of the island had contracted the disease [6]. Most of the reported cases of Zika between 2007 and 2015 occurred throughout islands in the Pacific [11] until May 2015 when the first case of Zika infection was reported in Brazil [25].

Zika poses a major health concern in part due to its connection to microcephaly. Microcephaly is a condition in which the brain and skull of a fetus do not develop properly, causing the child to be born with a small head and brain. Microcephaly can cause permanent mental

disabilities even when the fetus survives [7]. In several cases, the Zika virus was found in the brains of the fetuses, which suggests a strong association between Zika and microcephaly [18]. In 2015, the cases of microcephaly in Brazil increased from an average of 63 cases per year to over 1250 cases in 2015 [21]. In February 2016, the World Health Organization declared Zika a Public Health Emergency of International Concern [25].

Zika is also a global danger due to the prevalence of the vector, *Aedes aegypti*, in many regions of the world. The disease is typically spread globally by infected humans traveling and infecting mosquitoes in new areas of the world. In fact, this is how Dengue, a disease very similar to Zika and spread by the same vector, spread globally in the later half of the 20th century [4]. The spread of Zika is of special concern because of the Olympics held in Rio de Janeiro, Brazil in summer of 2016. The large influx of tourists to an area where Zika has been spreading rapidly over the past year presents a unique opportunity for the virus to spread even more rapidly than it otherwise could. This and the association between Zika and microcephaly make the 2016 Olympics an important factor to consider when examining the threat that Zika poses. The study of Zika is further complicated by the fact that approximately 80% of infected individuals are unaware of their infectious status [2]. Due to the lack of data on the spread of Zika, including lack of information regarding transmission and recovery rates, we develop an agent-based model with a variety of adjustable parameters to better understand how certain aspects of human and mosquito behavior throughout the Olympics may alter the spread of this disease.

¹Biology Department, University of Portland, Portland, OR,
²Mathematics Department, University of Portland, Portland, OR

Agent-based modeling

Before modern computers, trying to model how complex systems arise from individual interactions was impossible given the hundreds or thousands of computations that are needed to model every interaction. Instead, such systems were commonly modeled using a system of ordinary differential equations (ODEs). These models represent systems using a non-spatial approach with populations divided into different segments or compartments [20]. The classic example of this type of model regarding epidemic models is the SIR model, where individuals move from “Susceptible” to “Infected” to “Recovered” at certain deterministic rates. While ODE models are highly effective in many models of disease spread, this kind of model does not fit our goals. We wish to work with a model where the populations are heterogeneous and each individual may act independently from and differently than other individuals. We also need to take spatial aspects of individuals’ movements into consideration. Thus, the ODE modeling format, which works well for homogeneous and equally mixed populations, does not serve us well in our modeling effort [23].

Instead we have chosen to model Zika spread using agent-based models (ABMs). Rather than describing the system as a whole as ODEs do, ABMs model individuals, also called agents, and their individual interactions with one another and with their environment [6]. Agents can be people, animals, businesses, or anything with attributes, goals, or relationships. Agents are created individually as unique and autonomous entities [6]. By modeling individuals, ABMs can sometimes provide a more accurate representation of a real system. While populations have averages and traits as a whole, they are made of individuals that make choices. These choices are never the same throughout the system. Therefore, inherent to agent-based modeling is stochasticity, or randomness. Since the model relies on stochasticity, different outcomes can occur given the same input parameters. For this reason, the model should be run multiple times to obtain a full picture of the patterns and variations present in the model outputs.

Here we develop an ABM to explore the spread of the Zika virus. In general, the spread of infectious diseases is highly dependent on the underlying social networks. Diseases spread differently depending on how the hosts interact with each other [20]. In the case of vector borne diseases, such as Zika, the interaction between the host and vector is critical to understand.

The *Aedes aegypti* mosquito has been modeled previously in the hopes of understanding how other diseases, such as Dengue, are spread by this mosquito. In 2010, Almeida et al. developed a model of Dengue spread that focused on the importance of understanding the pop-

ulation dynamics, spatial elements, and the scheduling process of disease transmission. Their model consisted of mosquitoes, humans, animals, traps, and vegetation. While the movement of animals and humans was somewhat simplified, the model went into great detail into the life cycle of the mosquito and also included energy level, mating time, and successful biting rates. Upon completing the model, they tested various control measures for reducing the mosquito population [3].

Recently Manore et al. developed a hybrid model with a system of differential equations to explain vector behavior and an ABM to explain human behavior [17]. In their model, humans were allowed to travel to different areas (school, work, the park etc.) with varying levels of mosquito density. Among their conclusions was that greater levels of human movement led to an increase in disease spread. They also highlighted the importance of considering heterogeneity in mosquito movement to capture more realistic disease dynamics.

Perez and Dragicevic also emphasized the importance of spatial components for modeling the spread of infectious diseases and also used an ABM to model the spread of a communicable disease [20]. Here, the environment that the agents interacted with was constructed using geographic information systems (GIS), creating a realistic urban environment [20]. Results of this modeling effort provided insight into how the spatial interactions of individuals contributed to disease spread. In particular, after individuals commuted to highly populated areas, disease spread increased throughout populations with lower overall movement in their final destination, leading to higher incidence of disease in places such as schools and universities.

The purpose of our research is to better understand the Zika virus and how the 2016 Summer Olympics could affect the spread of the disease. Our model therefore builds upon the ideas and conclusions from these existing models, while also placing a specific focus on the spread of Zika throughout the city of Rio de Janeiro. Whenever possible, we use known rate parameters from similar mosquito-borne diseases, such as those for Dengue. Since many rate parameters remain unknown for Zika, we allow these to be defined and manipulated by the user. This enables us to focus our efforts on a sensitivity analysis on these parameters to determine the ways in which model parameters affect disease spread. Rather than create an artificial environment, we import several images of Rio de Janeiro into our model, with each image providing different information on the environment, mosquitoes, and humans. Both our vectors and hosts are modeled on the individual level, with the disease following an SEIR (Susceptible, Exposed, Infectious, Removed) progression.

Section 2 describes important aspects of the model such as the variables, input data, scheduling, initializa-

tion, and all submodels used. This in-depth description of the model allows any interested party to replicate our model for themselves. Section 3 outlines the experiments performed along with our results and is followed by a discussion of these results in Section 4. We end with final conclusions and areas for further research in Section 5.

2 The Agent-Based Model

In the following we provide details for our ABM of Zika spread using the formatting recommendations from the Overview, Design concepts, and Details (ODD) protocol for ABMs by Grimm et al. [9]. Our model is implemented in the agent-based modeling platform NetLogo [24].

2.1 Purpose

The purpose of our ABM is to simulate the spread of the Zika virus in Rio de Janeiro during the 18 day span of the 2016 Olympics in order to gauge the extent to which an influx in tourism may affect disease spread. We considered various aspects of known mosquito behaviors, expected tourist and local behaviors, and as much knowledge of the disease characteristics as was available at the time of our study. Simulation results provide some initial insight into how certain mosquito and human characteristics might change the severity of disease spread.

2.2 Entities, State Variables, and Scales

There are two kinds of agents in the model: mosquitoes and humans. They each have their own sets of variables and counters, including Boolean variables for each infection state. At any point in time, mosquitoes and humans may reside in one of four states: Susceptible (they have not yet contracted Zika but are not immune), Exposed (they have contracted Zika but are not yet able to infect others), Infectious (they have contracted Zika and can spread the disease to other Susceptible individuals), or Removed (they have either died or recovered from Zika and can no longer spread it to others). We note here that due to their short lifespan mosquitoes are assumed to enter the Removed compartment only upon death, as they do not have enough time to recover. If a Susceptible agent becomes infected, it will move into the Exposed state and an exposed counter is started for that agent. Once the exposed counter reaches its limit, the agent moves to the Infectious state. If the agent is human, an infectious counter is started, and once this counter reaches its limit, the agent becomes Removed. Mosquitoes have no such counter, as they are assumed to remain infectious until they die.

Mosquitoes have variables for their age and the type of environment (known as a “patch”) that they will be ini-

tialized on. Mosquitoes can be initialized on vegetation, favela, hotel, or residential patches and the type of patch to which they are assigned is determined stochastically. Mosquitoes will only be initialized on their assigned patch type if they have completed the larval stages of development. If they have not completed the larval stages, they will be initialized on a patch separate from the human population until they have completed the larval stages.

Humans are divided into two groups, locals and tourists, each of which have variables for the kinds of patches they are initialized on, including hotels, favelas or other residential zones. If a human is labeled as a local, they are initialized on a favela or other residential zone patch and will follow a daily pattern of moving to a random patch and moving in a random way that is slower than tourist movement. In the evening, they return to their home patch. Humans labeled as tourists are initialized on hotel patches and will move to patches nearby or in Olympic arenas during the day. They then return to their assigned hotel patch at night. Tourists choose which location they are traveling to every morning based on a predetermined probability of tourists visiting each site. Their options include five Olympic regions and the Christ the Redeemer hike. Stadiums that hold more events with larger audiences are more likely to be attended by the tourists. Athletes and their coaches are included in the tourist group because their behavior is fairly similar, and there is only a very small proportion of athletes compared to the rest of the population.

Locals are initialized on patches within a two mile radius of the Olympic areas and are more likely to be initialized on patches with higher human densities. They move around the area that they are initialized in and occasionally go to Olympic events. The decision for a local to go to an Olympic region is probabilistic, with every local having a 20% chance of choosing to attend an event on a given day. There were no specific values for this percentage in the literature, so this is an estimation of the number of locals interested in and able to attend events. Locals determine which event to attend in the same way as the tourists.

Our environment consists of a rectangular region of Rio de Janeiro where all Olympic events and main tourist attractions take place. The total area modeled is 1370 by 845 patches. Patches represent an 88 by 86 feet two-dimensional area of land, so that the entire modeled area is 22.83 by 13.76 miles. The model is updated every minute. Patches have many variables associated with them including if the patch consists of water (lake or ocean), vegetation, how densely populated the area is by locals, if it is part of a favela, and if it is part of an Olympic region. Human and mosquito agents are able to access patch variables to help determine their behavior.

Several variables can be manipulated by the user.

These include: number of humans (80% are designated as locals and 20% as tourists), number of mosquitoes, the exposed time of the infection for both humans and mosquitoes, the infected time of humans, the biting success rate for mosquitoes, the infection chance, percentage of initially infected locals or mosquitoes, percentage of initially exposed locals or mosquitoes, and percentage of initially removed locals. All tourists are assumed to initially be susceptible.

2.3 Process Overview and Scheduling

Mosquitoes move: Mosquitoes are initialized on patches based on their assigned patch type and, unless involved in another activity, will move randomly within a 5-patch radius of their starting location [13]. If it is between 17:00 (5 P.M.) and 21:00 (9 P.M.) on any given day, mosquitoes will travel further in each tick to model increased activity around dusk [12]. At the beginning of every day, mosquitoes who have completed the larval stage will move to a patch of their designated type and set that patch as their home patch.

Biting: If a mosquito has successfully found a human, meaning it is within sensing range of the human, the mosquito will attempt to make a successful bite, which is modeled stochastically using the user-defined `bite-success-rate` parameter. If the bite is successful, then the disease states of both the human and the mosquito are inspected to see if infection can occur. If one agent is susceptible and the other is infected, then a stochastic determination is made to see if the susceptible agent moves to the exposed state. This chance is governed by the parameter `infection-chance`.

Death of mosquitoes: At every age, mosquitoes have a certain chance of dying, and this chance increases as the age of a mosquito increases: 8% chance for age < 5; 10% for $5 \leq \text{age} < 10$ days; 15% for $10 \leq \text{age} < 15$ days; 25% for $15 \leq \text{age} < 20$ days. The longest a mosquito can live in our model is 21 days. These values were chosen so that death probability increased with age and also in order to maintain a stable mosquito population.

Emergence of mosquitoes: Once every day, 11% of the original number mosquitoes will hatch new mosquitoes on an oviposition site, which is located away from human and mosquito populations. Eleven percent was chosen because it keeps the total mosquito population the most stable at all of the mosquito populations tested. The new mosquitoes will stay on the oviposition site for 5 days to represent the aquatic stages of mosquito development. Once a new mosquito has reached the end of the larval stage, it will emerge as an adult female mosquito;

these are the only mosquitoes included in the model as they are the only mosquitoes that bite humans [5]. We assume all male mosquito processes, but do not model them explicitly. The procedures involved in mosquito life cycle and movement are depicted in Figure 1.

Update disease status and counters: The disease states and disease state counters of each agent are updated. The age counter of mosquitoes is updated, and the time and date is updated. Change of disease state, age, or counters does not affect movement of agents. Changing the disease states of humans does not alter their movement because the majority of people who become infected with Zika do not experience symptoms [2]. Further, of those who do experience symptoms, they would either not show severe enough symptoms to significantly alter their movement or would not show symptoms until after the 18 day scope of the model.

Locals move: Locals' movement during the day is randomly decided, but slower than random tourist movement. Locals move within a two-mile radius of the Olympic areas and stay out of water and vegetation areas. At Olympic event times during the day, each local has a 20% chance of attending a nearby event. After the event is concluded, the locals who attended return to moving randomly. At 22:00 locals return home. Figure 2 provides a flow chart for locals' procedures.

Tourists move: Tourists are initialized on a hotel patch and each day will pick an Olympic region or decide to hike to the Christ the Redeemer statue. If they choose an Olympic region, before arriving at their destination at 10:00, each tourist calculates the time it will take to travel to their destination, based on distances obtained from Google Maps, and will leave their hotel at the appropriate time. For simplicity, a tourist moves from the hotel to a mosquito-free zone for the necessary travel time. Once this time has elapsed, they then immediately move to their destination patch. With this process, we assume no infection transmission is possible in transit. Since the distance from the hotels to Olympic regions is not within walking distance, it is reasonable to assume little to no infections happen while tourists are traveling in vehicles. Throughout the day tourists move randomly within a given radius of the Olympic region when Olympic events are not taking place. If an Olympic event is occurring, tourists will move to the location of the event instead of moving randomly, and they will remain in the Olympic arena for the duration of the event. We set all events to last one hour. At 22:00 tourists will return to the hotel patch that they were initialized on, after stopping in the mosquito-free zone for the required amount of time to travel back to the hotel. Tourists can only move

to or on certain types of patches, such as hotel, Olympic region and surrounding patches, and patches along a hike to Christ the Redeemer. Figure 3 provides a flow chart for tourists' procedures.

The model is updated at one-minute intervals, called *ticks*. Figure 4 provides an overview of the entire scheduling process.

2.4 Design Concepts

Basic principles

In order to create the model, we utilized knowledge from previous models of infectious diseases. The Zika virus progresses similarly to an SEIR model where both the host and the vector advance through different stages depending on whether and when the individual contracts the disease. In addition to the progression of the virus, the spread of the virus primarily depends on interactions between human and mosquitoes. Other factors that play a role in disease spread include the individual movements of locals and tourists during the Olympics.

Emergence

Disease spread is the emergent behavior captured in our model and is governed by individual behaviors and characteristics of the humans and mosquitoes. Although agent behaviors and decisions are strictly defined, stochasticity is present in each.

Sensing

Mosquitoes are able to sense humans within about 100 feet [10]. This is the most important form of sensing in our model. Humans have the ability to sense all patch variables including patch color, population density, and attraction location. Mosquitoes also have the ability to sense patch variables such as favela patches and vegetation and water patches.

Interaction

Humans and mosquitoes interact during the biting procedure. Mosquitoes interact with other mosquitoes when they lay eggs, which eventually become new mosquitoes. This interaction is important, as it enables transovarial transmission, disease transmission from mother mosquito to baby mosquito [15]. Other human-human and mosquito-mosquito interactions are assumed, but not modeled explicitly.

Stochasticity

Many procedures in the model involve at least some stochasticity. The number of tourists who move to each attraction is a stochastic process, as is the time humans move to the Christ the Redeemer hike. Biting and disease transmission are both stochastic procedures controlled by a user-controlled slider. Mosquito death is also a stochastic procedure with the probability that a mosquito dies increasing as the mosquito's age increases. When humans are not at home or their hotel or watching the events, they are moving around randomly.

Collectives

Tourists, locals, and mosquitoes are collectives of agents who each have different home locations, movement patterns, and variables. Tourists move primarily between attraction locations and hotels, and locals move randomly at a slower rate than tourists and return to their home patch at night. At certain times of day, tourists will move to events and some locals will join them. Mosquitoes are initialized on a start patch once they reach adulthood and move randomly within a 5-patch radius of that patch for the entirety of their lifespan.

Observation

We are primarily interested in the percentage of the population (locals and tourists) that contract the disease over the time course of 18 days.

2.5 Initialization

There are two important aspects of model initialization: the environment and the placement of the agents. Four images are used to create the environment and its properties. Each image is loaded into NetLogo, and patch variables are defined based on the color of each patch on a given map. First, a map of the favelas is imported [22]. The same favela map is used to create a separate Olympic region map that is imported next. In this map, we have recolored each Olympic region (which were all the same color in the favela map), so that humans can choose a particular region to visit based on the patch color. The third map to be imported is a human population density map of the city of Rio de Janeiro to determine where locals are more likely to be initialized [14]. Finally, a Google map image is imported to determine the areas of large standing bodies of water, the ocean, and patches of dense vegetation [8].

After the environment is initialized, the agents are initialized. Mosquitoes are initialized first, with half of the mosquito population on vegetation patches within a radius of 125 patches of event locations, 30% of mosqui-

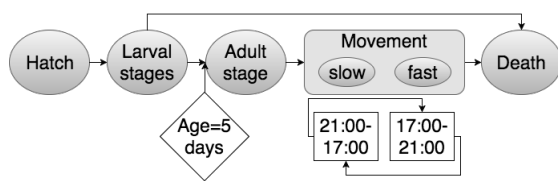


Figure 1: Flowchart for mosquito daily activities.

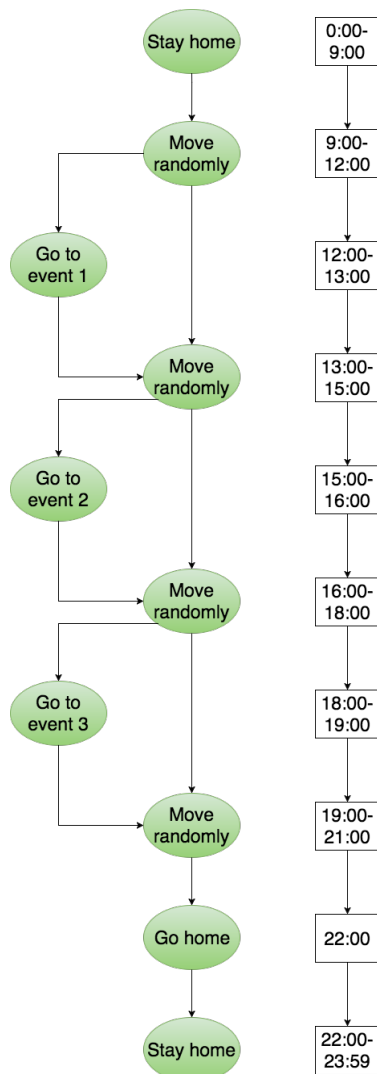


Figure 2: Flowchart for locals, which outlines the activities that locals can perform each day and when these activities are performed.

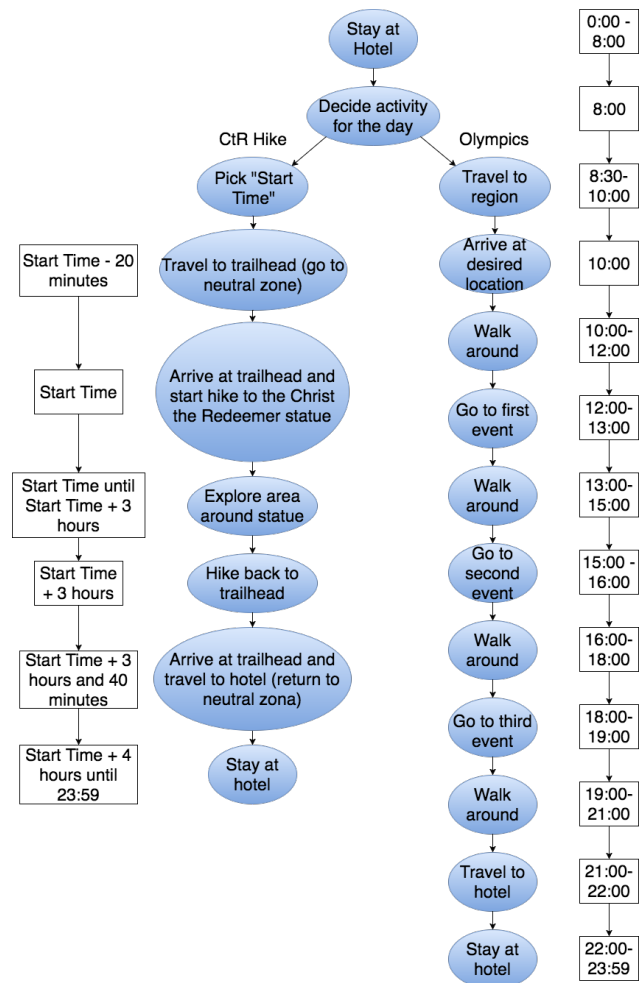


Figure 3: Flowchart for tourists, which outlines all the possible activity options for a tourist each day and when tourists perform each of these activities.

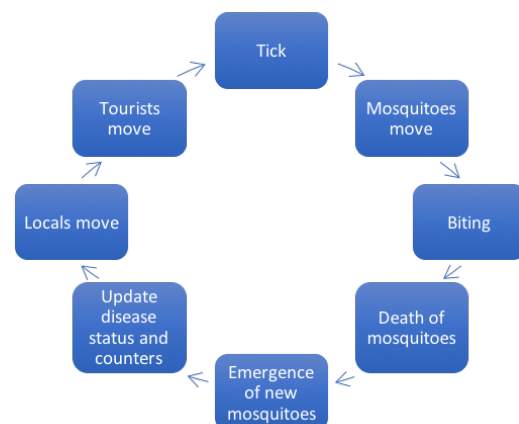


Figure 4: Schedule of processes performed each minute (tick).

toes on favela patches within 125 patches of event locations, 15% initialized on any patch within 125 patches of event locations, and 5% of mosquitoes initialized on hotel patches. For one experiment we did not allow mosquitoes on hotel patches in order to examine whether mosquitoes on hotels significantly changes outbreak severity. In this case, the percentage of mosquitoes initialized on a patch within 125 patches of event locations is increased from 15% to 20%. The 125-patch radius was chosen since we are only interested in modeling disease spread in relation to an increase in tourists near Olympic regions, and we therefore only concern ourselves with mosquitoes who can come into contact with humans who are near Olympic venues. We assume here that tourists do not venture out further than a 120-patch radius from Olympic venues. We also do not allow any agent, human or mosquito, to enter the ocean; thus, Zika is not allowed to be transmitted on ocean patches. In all experiments, locals are initialized on patches within 120 patches of event locations with 45% of locals on high density patches, 25% of locals on medium-high density patches, 15% of locals on medium density patches, 10% of locals on medium-low density patches, and 5% on low density patches. Exact values for these percentages were not found in the literature, so these numbers are estimates based off of the human population density map [14]. Tourists are initialized on hotel patches.

2.6 Input Data

As mentioned in the initialization section, four images are used to create the environment and its properties. Each image is loaded into NetLogo and variables are defined based on the color at each patch. The map shown in Figure 5 provides information on which patches are to be labeled as a favela patch (light and dark purple patches) [22]. Favela regions are used as input data because mosquitoes who are initialized in residential areas are more likely to be initialized in a favela due to housing conditions such as open windows without screens, suboptimal water flow, and higher densities of vegetation nearby [16]. Other colors and details in this version of the map are not used in the model.

From the favela map in Figure 5, we create a map of the Olympic regions, where each region is coded using a different color so that locals and tourists can decide which events they wish to attend (Figure 6). There are five different Olympic regions, referred to as **stadium-clusters** in our model. The first is teal, the second is green, the third is red, the fourth is blue, and the fifth is yellow. Stadium-clusters are used in local and tourist procedures involving decisions and movement throughout the day.

A human population density map of the city of Rio de Janeiro (Figure 7) is imported to determine where locals

are more likely to be initialized [14]. As human population density increases, the colors in the map move from a dark red to bright yellow. There are five different human densities set from this map: **low**, **med-low**, **med**, **med-high**, and **high**. A probability distribution was determined through observation that sets the likelihood of a local being initialized on a patch with a specific density. Note in the map that grey areas are considered to have no humans, and thus, locals do not initialize on any grey patches.

A Google map image is imported to determine the areas of large standing bodies of fresh water, the ocean, and patches of dense vegetation [8]. Once the Google image was saved, modifications were made to color the ocean purple to create a difference in color between the ocean and freshwater. Once the image is imported, a range of shades of light green areas are set to **vegetation**, blue areas to **water**, and purple areas to **ocean**. The resulting map is shown in Figure 8.

Once all four maps are imported, more variables are initialized and some previously initialized variables are recolored since they were colored over by 'newer' images. **Vegetation** is set to green, **water** is set to a dark blue, **favela** is set to a light orange, **ocean** is set to a light blue, and **Olympic** areas are recolored as magenta. Since none of the imported maps include hotels, a simplified **hotel** region is hardcoded into the environment. The size of the hotel region is 18 by 4 patches, or approximately 545,000 square feet and is located in the Copacabana district, where the majority of tourists stayed during the Olympics [1]. Since we are interested in modeling spread of Zika due to tourist activity near Olympic regions, a 120-patch radius (approximately 2 miles) around each Olympic region, shown in cyan, is also hardcoded to denote locations where agents are allowed to reside. Locals are initialized in this radius and tourists are not allowed to travel outside these cyan areas. This is due to model limitations for number of locals and a reasonable travel radius for tourists during the day. The completed environment used for the model is shown in Figure 9.

2.7 Submodels

Submodels were individually tested in a simplified environment. Individual agents were observed for several model days to ensure the agent was performing tasks correctly. When relevant, state variables of agents were monitored as well. For instance, when testing the infection procedures, infection states of several mosquitoes and humans were monitored during each run to ensure that infection was progressing properly. As new submodels were added to the model, they were tested using the same procedures. Below we list and explain the function of each submodel.

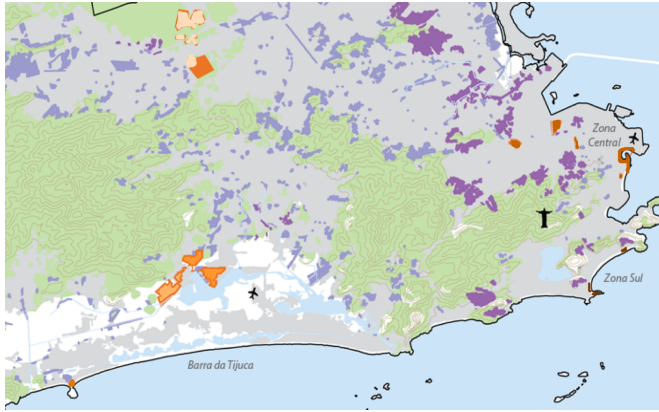


Figure 5: Favela map. Favelas are shown in light and dark purple.

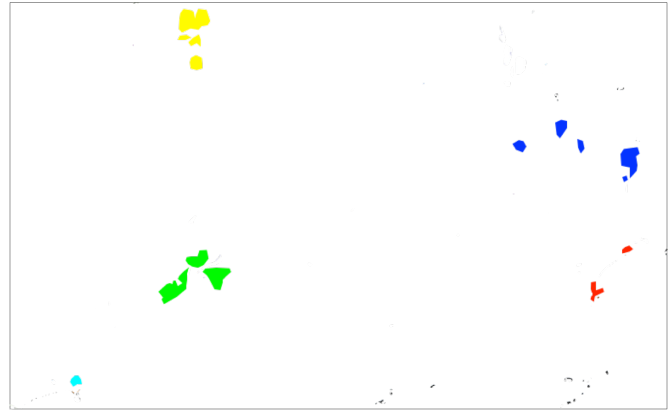


Figure 6: Map for the Olympic regions. Each region is depicted by a different color.

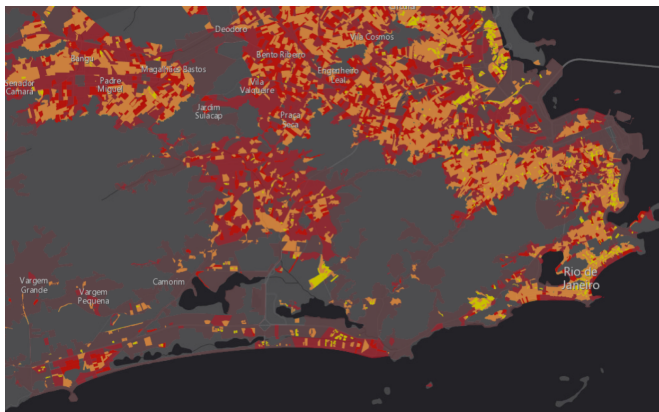


Figure 7: Human population density map of Rio de Janeiro. Yellow = highest; Orange = Very high; Bright Red = High; Dark Red = Low; Darker Red = Very Low; Grey = Lowest.

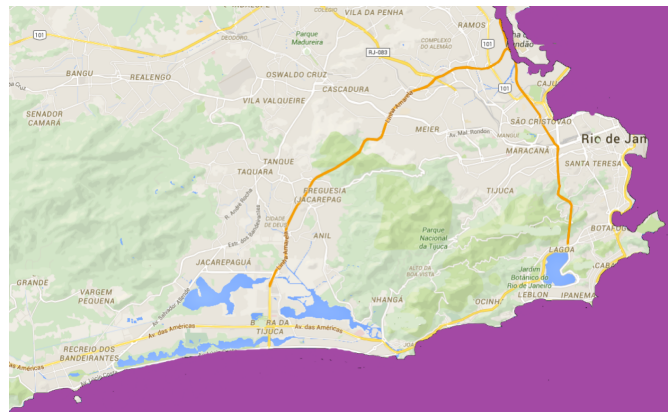


Figure 8: Google map for differentiating vegetation, water, and land. The ocean is shown in purple, while other water is shown in blue. Vegetation patches are in various shades of green. Land is shown in grey.

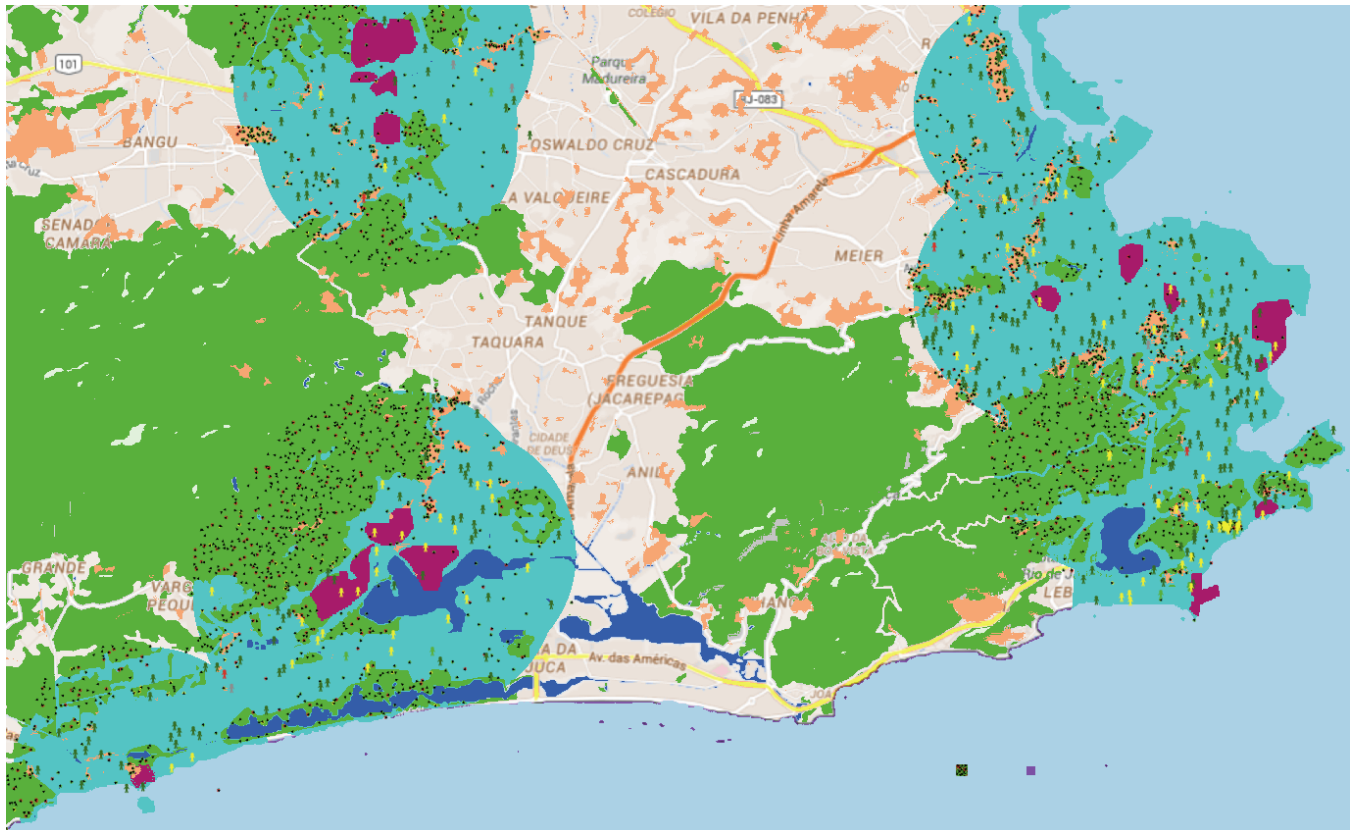


Figure 9: Final view of the “world” window in the NetLogo interface once all maps have been imported. **Vegetation** is green; **water** is dark blue; **favelas** are light orange; the **ocean** is light blue; and **Olympic** areas are magenta. The **hotel** region is hardcoded in and colored violet (though in this figure it is covered up by tourists). The 2-mile radii around each Olympic region in which agents are allowed to travel are shown in cyan. The two square regions in the lower right of the figure indicate the oviposition site for mosquitoes (left) and the neutral zone for tourists (right).

Move-m (mosquito movement): If the age of a mosquito is 5 days and it is 0:00 (midnight), the mosquito will choose a patch based on its cluster number, which is the same as the cluster number of its parent mosquito. This means that as mosquitoes emerge into the adult stage, they will move to the same type of patch as the mosquito who hatched them. Mosquitoes who are 5 days old or older will then move in a semi-random way. If they are within 5 patches of their starting patch, they will pick a random direction and move forward 0.1 patches, or approximately 9 feet in one tick (one minute). If they are more than 5 patches away from their starting patch, they will turn 180 degrees and move forward 0.1 patches. If it is between 17:00 and 21:00, mosquitoes double the distance they travel in each tick to simulate increased activity at dusk [12]. Five patches is approximately 440 feet, which is at the edge of the typical range of a mosquito [13]. The patch distances 0.1 and 0.2 (about 9 feet and 18 feet respectively) were chosen because they keep mosquitoes from straying very far from the patch on which they were initialized, which is consistent with the behavior observed in Harrington et al. [13].

Infect-m-to-l (infection of locals by mosquitoes): Mosquitoes can sense humans within a range of about 30 meters [10], which is about 98 feet. We simplified this in our model to the width of one patch, or about 88 feet. Therefore, if an infectious mosquito is within a distance of 88 feet from a local, the mosquito will attempt to bite the local. It is thus possible for a mosquito to bite a local who resides on the same patch or on a neighboring patch, as long as the total distance between the mosquito and the local is within 1 patch width. The chance that the bite will be successful is user-defined through the parameter `bite-success-rate`. If the bite is successful and if the local was susceptible, there is a chance that the local will become exposed (infected but not yet infectious). This chance is also user-defined through the parameter `infection-chance`. In all of our experiments we keep `infection-chance` = 0.33 to match the value determined by Manore et al. [17]. If the local becomes exposed, they will set their exposed counter (which keeps track of the latency period) to zero days.

Infect-m-to-t (infection of tourists by mosquitoes): This procedure is identical to the Infect-m-to-l procedure, only it governs a mosquito's ability to infect tourists instead of locals. We assume that the parameter values for `bite-success-rate` and `infection-chance` are identical for locals and tourists. Our model environment is two dimensional, which allows mosquitoes to sense and reach an unrealistic number of humans if they reside in buildings with multiple stories. For example, at hotels where tourists are very concentrated but are

often on separate floors, our model will simulate multiple tourists on the same two-dimensional patch, when in reality they might just be in a room directly above or below another tourist. This could mean that too many tourists become infected at hotels if there is even one infectious mosquito there. To test this theory, we ran an additional experiment using default values of all parameters (see Table 1) on a version of the code that did not allow mosquitoes on hotel patches and compared it to the original model with default values. See the Results and Discussion section for details.

Infect-l-to-m (infection of mosquitoes by locals): If a mosquito is within one patch (roughly 88 feet) of an infectious local, the mosquito will attempt to bite the local. The chance that the bite will be successful is user-defined through the parameter `bite-success-rate`. If the bite is successful and the mosquito is susceptible there is a chance that the mosquito will become exposed. This chance is also user-defined and controlled by the same parameter dictating infection chance from mosquito to human, `infection-chance`. This parameter value, set to 0.33 in our experiments, is the same as the one assumed in Manore et al. [17]. If the mosquito becomes exposed, they will set their exposed counter to zero days.

Infect-t-to-m (infection of mosquito by locals): This procedure is identical to the Infect-l-to-m procedure, only it governs a mosquito's chance of becoming infected by tourists instead of locals. Again, we assume that the parameter values for `bite-success-rate` and `infection-chance` are identical for locals and tourists.

Age-up (mosquito aging): At the beginning of every day, except on the first day of life, all mosquitoes increase their age by 1 day.

Death (mosquito death): At the beginning of every day, except on the first day of life, mosquitoes have a chance of death based on their age. The probability distribution of death at every age was set in order to keep the total mosquito population stable. This distribution was discussed in Subsection 2.3.

Birth (mosquitoes laying eggs): Every day at 10:00, 11% of the initial number of mosquitoes will hatch a new mosquito. 11% was chosen because it kept the mosquito population the most stable at all of the initial mosquito population sizes that were tested. If the parent mosquito is susceptible or exposed, the new mosquito will be susceptible. If the parent mosquito is infectious, the new mosquito will also be infectious. New mosquitoes begin at age 0 and will reside in a human free zone until their

age reaches 5, at which time they will move to a patch in their parent mosquito's cluster.

Change-disease-state-m: This mosquito procedure, evaluated at every tick, updates the disease status of mosquitoes. A counter variable, `exposed-counter-m`, is used to track the amount of time the mosquitoes are exposed. Once `exposed-counter-m` crosses a given threshold, mosquitoes move from exposed to infectious and remain infectious for the remainder of their lifespan. The latency period threshold value was not found in the literature for Zika but is assumed to be similar to that of Dengue Fever which infects the same type of mosquito [4].

Change-disease-state-l: This local procedure, evaluated at every tick, updates the disease status of locals. A counter variable, `exposed-counter-l`, is used to track the amount of time the local is either exposed or infectious. Once `exposed-counter-l` crosses the appropriate threshold, the local moves to the next stage of the disease, either infectious or removed. Human exposed and infectious periods of time were not found in the literature for Zika and, as above, are assumed to be similar to those of Dengue Fever [4].

Change-disease-state-t: This tourist procedure, evaluated at every tick, updates the disease status of tourists. It is identical to the Change-disease-state-l procedure above, only it targets tourists instead of locals.

Pick-location: A tourist procedure called at the beginning of each day to determine which Olympic region each tourist will choose to travel to that day (See Figure 6) or whether they will choose instead to hike to Christ the Redeemer. The decision is based off of a set probability distribution determined by the average number and size of events held in each Olympic region and the average number of tourists expected to visit Christ the Redeemer. The more tourists that are expected to attend events in a particular region, the higher the probability a tourist will select that region. After making their decision, each tourist is assigned a movement time, based on distances determined through Google Maps, that it will take for them to get to that stadium cluster from the hotel or they are assigned a time to which they will begin their hike to Christ the Redeemer.

Move-to-event-region: A tourist procedure that moves tourists, those who will attend Olympic events, from their hotels to a mosquito-free patch, the "neutral zone", and then to their chosen Olympic region. The time it takes to travel to their desired location is predetermined in the Pick-location submodel, and each tourist

is placed in the neutral zone, where they cannot be bitten, for the required amount of travel time determined by average travel time in Google Maps [8]. Tourists move to the neutral zone at 10:00 minus the travel time. At 10:00, the tourists are moved from the neutral zone to the Olympic region that they decided to visit that day.

Christ-the-redeemer: A tourist procedure that determines when and how a tourist will visit the Christ the Redeemer statue. Based on the tourist's event decision, a tourist will have a probability to visit the statue once per day. If the tourist decides to go, they will first pick a "Start Time" to visit the statue from 5 options: 9:00, 11:00, 13:00, 15:00, and 17:00. This time is chosen in the Pick-location submodel. The tourist will move to the neutral zone for 20 minutes (the average time it takes to get from the hotel area to the trailhead) prior to their chosen Start Time and move to the starting point of the hike at their chosen Start Time. Then, the tourists move towards the statue with a bit of stochasticity along the way. After staying at Christ the Redeemer for a given amount of time, the tourists return to the beginning of the hike and back to the hotel in the same way as they moved to the statue. The entire process takes 4 hours, and tourists will spend the rest of the day on their hotel patch.

Move-throughout-region: A tourist procedure that allows tourists to move randomly throughout a 2-mile radius of their chosen Olympic region whenever Olympic events are not taking place. This procedure prevents travel into water, ocean, or vegetation patches.

Watch-event: A tourist movement procedure that moves tourists from the 2-mile radius to the event that they decided to go to that day, if they chose to attend an Olympic event instead of the Christ the Redeemer hike. The procedure is designed so that the locals who are at Olympic events are not moving for the hour long event. This procedure is called three times a day, at 12:00, 15:00, and 18:00.

Movement-l: A movement procedure for locals that allows them to move randomly at a slower rate than random movement of tourists but prevents travel into water, ocean, or vegetation patches. The procedure is designed so that the locals who are at Olympic events are not moving for the hour long event.

Local-event: A movement procedure for locals. If the local decides to attend an Olympic event that day, this procedure will move them to their chosen event at the

appropriate time. This procedure is similar to the tourist Watch-event procedure.

Print-time: A procedure that prints the hour and day every 60 ticks. This procedure is used for testing purposes to ensure that events and procedures are happening at the right time.

Travel-to-hotel: A tourist procedure that determines how long it will take for each tourist to return to the hotel where they are staying each night. Once each tourist determines the time it will take, they are moved to a patch outside of the city, a neutral zone, at 22:00 minus the traveling time.

Go-home: A local procedure that is called at 22:00 every day, where all locals return to the patch on which they were initialized. We assume this is an average time at which all locals return to their home.

Go-to-hotel: A tourist procedure that is called at 22:00 every day, where all tourists return to the hotel patch that they were initialized on. We assume this is an average time that all tourists would return to their hotel.

Table 1: Default values of user-defined parameters.

Parameter	Default Value
number-of-humans	400
number-of-mosquitoes	400
exposed-time-m	14400 (minutes)
exposed-time-h	7200 (minutes)
infected-time-h	7200 (minutes)
bite-success-rate	0.50
infection-chance	0.33
%-initially-infected-m	5%
%-initially-infected-l	1%
%-initially-exposed-m	5%
%-initially-exposed-l	1%
%-initially-recovered-l	3%

3 Results and Discussion

To investigate the spread of Zika in Rio de Janeiro throughout an 18-day span of Olympic-related tourist travel, we ran six experiments varying key parameters of interest. In the first five experiments we monitored the percentage of locals and tourists who experienced infection at some point during the 18 day time course. The first four of these allowed mosquitoes on hotel patches, while the fifth did not. The first experiment tested four

levels of initially infected mosquitoes; the second tested three levels of the bite success rate; the third and fourth experiments tested four levels of population size of humans and mosquitoes, respectively; the fifth tested effects of mosquitoes on hotel patches; and in the final experiment we monitored infection of locals only, as we were testing the effect of the presence or absence of tourists on the infection of locals. The first four experiments were run 60 times, the fifth was run 20 times, and the last 100 times. The data in each case followed an exponential distribution, and error bars are represented with 95% confidence intervals.

Figures 10–13 reveal results from varying four key parameters, one at a time, while keeping all other parameters at their default value (Table 1). Figure 10 shows that as the percentage of initially infected mosquitoes increases, the average percentage of infected humans increases linearly (slope of 3.4% for tourists and 1.3% for locals). This is not surprising, because the percentage of initially infected mosquitoes is expected to proportionally affect the probability that a susceptible human will encounter an infectious mosquito.

In Figure 11, the mean percentage of infected humans remains fairly constant. This unexpected result suggests that biting rates may play a minor role in the spread of Zika. One explanation could be that in our model a mosquito is allowed continued biting attempts as long as the human has not moved outside the mosquito's range. This result could also suggest that if humans remain fairly inactive, mosquitoes may still have the same likelihood of transmitting disease, even if their biting rates are lower.

Figures 12 and 13 report changes in infection spread due to variations in the population sizes of humans and mosquitoes. Due to limitations in computation time (each simulation took approximately 90 minutes to run), which was compounded as number of agents increased, determining how infection scales with population growth is a critical component of our analysis. While the number of humans (locals + tourists) seems to have little effect on disease spread (Figure 12), an increase in the mosquito population produces a linear increase in disease spread, for both locals (slope = 2.1%) and tourists (slope = 7.4%) (Figure 13). The latter result is expected, as it is consistent with the finding that the basic reproductive number increases as mosquito density increases [17]. However, the former is another unexpected result and will be a focus for further investigation.

As mentioned earlier, one concern with our model construction came from the fact that we have a two-dimensional model, where we must model a building with multiple levels as a two dimensional cluster of patches. Therefore, when tourists are in their hotels, the model will place tourists who are directly above or below one another all on the same patch. The fifth experiment therefore

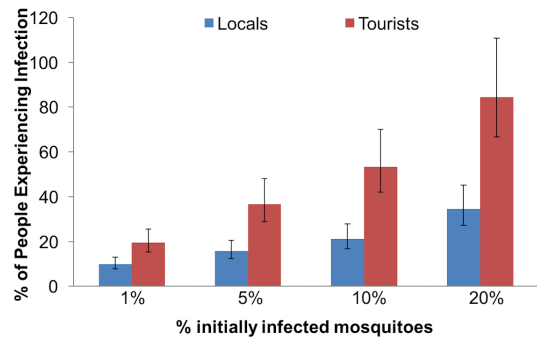


Figure 10: Human infection percentage for locals (left) and tourists (right) vs percentage of initially infected mosquitoes. Heights of bars represent means from 60 simulations. Error bars represent the 95% confidence intervals.

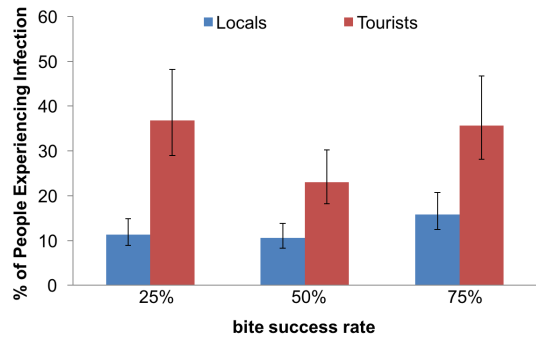


Figure 11: Human infection percentage for locals (left) and tourists (right) vs **bite-success-rate**, which controls the probability that a mosquito has a successful bite. Heights of bars represent means from 60 simulations. Error bars represent the 95% confidence intervals.

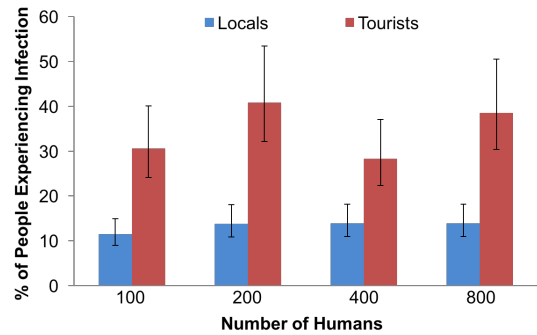


Figure 12: Human infection percentage for locals (left) and tourists (right) vs human population. Heights of bars represent means from 60 simulations. Error bars represent the 95% confidence intervals.

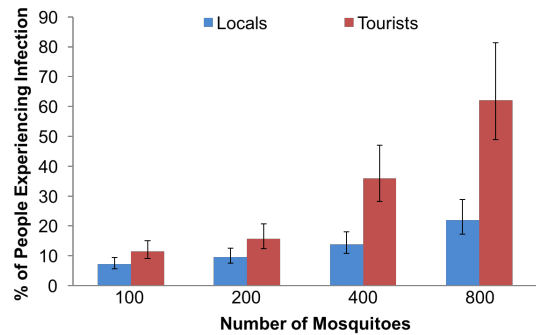


Figure 13: Human infection percentage for locals (left) and tourists (right) vs number of mosquitoes. Heights of bars represent means from 60 simulations. Error bars represent the 95% confidence intervals.

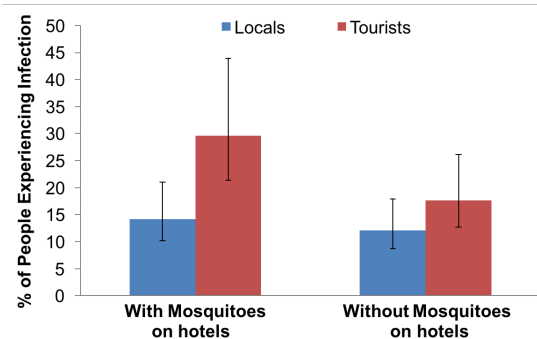


Figure 14: Human infection percentage for locals (left) and tourists (right) with and without mosquitoes on hotel patches. All parameters are fixed at their default values (Table 1). Heights of bars represent means from 20 simulations. Error bars represent the 95% confidence intervals.

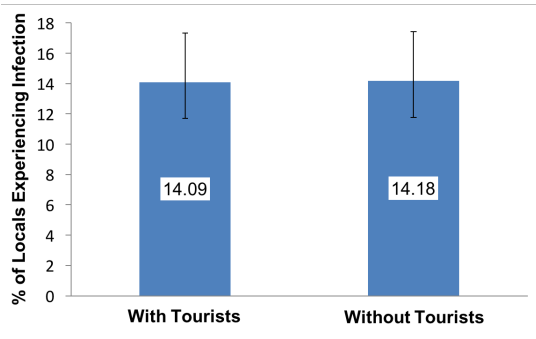


Figure 15: Local infection percentage with and without tourists. All parameters are fixed at their default values (Table 1). Heights of bars represent means from 100 simulations. Error bars represent the 95% confidence intervals.

tested the possible effects of mosquitoes having access to larger than realistic numbers of tourists on hotel patches by comparing a version of the model that did not allow mosquitoes on hotel patches to the original model, which did allow mosquitoes on hotel patches. All other model components were the same, and parameters were fixed at their default values given in Table 1. As shown in Figure 14, there may be a slight decrease in tourist infections when mosquitoes are restricted to non-hotel patches, and a one tailed t-test for the difference in means with unequal variance revealed a significant difference in the percentage of tourist infections (p -value = 0.03). This is therefore a focus of further study.

In the final experiment, we tested the effects of tourists entering the city on the infection rates of locals. Figure 15 reveals no significant difference in the local infection percentage, with or without the presence of tourists. Thus, our model predicts that the influx of tourists during the 18-day span of the Olympics should have little effect on the overall spread of Zika in Rio de Janeiro. At the same time, from the previous results, we can still see that the tourist population may be significantly affected.

Altogether, these results suggest that disease spread is most sensitive to the number of infectious mosquitoes, controlled either by total mosquito population or percentage of mosquitoes who are initially infectious. Thus, in order to reduce the spread of the Zika virus and other vector-borne diseases, it might be most beneficial to focus on reducing the number of mosquitoes with the disease rather than reducing human population in certain areas.

4 Conclusions and Future Work

We present here an agent-based model of the spread of Zika during the 18-day span of Olympics-related tourist travel to Rio de Janeiro in 2016 to better understand the role that humans and mosquitoes play in transmission of this disease. While the results of our modeling effort do not directly affect spread of the virus due to the Olympics, they do provide a platform upon which we may make predictions on the spread of Zika or other mosquito-borne diseases in other areas hosting world-wide events. Future research will include an extension of our current model to make predictions on how the infections experienced by tourists may affect spread of Zika world-wide, as tourists return to their home country.

There exist many unknowns concerning Zika transmission, prevalence, and best control measures. To date, the authors are unaware of any publicly available data to which we can compare our model outputs. Due to the lack of specific information on Zika, we have tested a variety of scenarios, to make predictions on how human and mosquito behaviors, controlled by certain model parameters,

may affect outbreak levels and to better gauge reasonable levels for such parameters. Though our initial results are intriguing, there is much room for improvement of our model.

One modification we have begun to investigate involves the activity of mosquitoes in hotels. In the current version of our model, mosquitoes can bite humans throughout the day, even in hotels. This increases the probability of a human becoming infected, especially during the evening when humans are not as active. A revision to our current model should provide more insight into transmission outside of the hotel area, by prohibiting mosquito bites in hotel areas. Preliminary results without mosquitoes on hotels indicate some difference in overall infections (see Figure 14 and our discussion in Section 3).

We would also like to test wider ranges of our model parameters and perform a global sensitivity analysis (changing more than one parameter at a time) to get a better sense of how sensitive the model output is to each model parameter. This would allow us to find more realistic values for unknown parameters. It is also important that parameters be updated as more information is collected regarding Zika transmission in order to increase the accuracy and utility of the model.

Future iterations of the model will include the ability to predict how outbreaks, such as an outbreak in Rio, affect the spread of the disease in other susceptible countries and will also investigate how adaptive behaviors of humans can help reduce the spread of Zika. Some specific adaptive behaviors that could be added to our model include changes in human behavior to avoid mosquitoes if they have encountered mosquitoes previously, mosquito population control measures such as reduction of oviposition sites, and healthcare seeking behaviors if infection is suspected.

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